



Simulation Model to Understand Nurses' Fatigue Level in an Intensive Care Unit

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Abstract. Although nursing is physically and mentally strenuous, only a few studies have been done to find the impacts of the fatigue level and nursing workflow corresponding to major healthcare activities in an intensive care unit (ICU). To address this need, the current study aims to understand the relationships among the key nursing activities that impact their fatigue levels in ICU. Nurses' time-study and real-time location data have been used to develop a simulation model in two different periods: February to March 2020 and July 2020. Two Hierarchical Task Analysis charts were developed from the collected data, one for each period, and used as the foundation for the fatigue-recovery simulation model. Different scenarios of all nursing activities' frequencies (number of conducted tasks during a shift) and task sequences (number of times tasks are conducted continuously prior to a break) were simulated in order to understand their impact on nurses' predicted average fatigue level reached in a shift. According to the results, the performing procedure, patient care, and peer support activities stand out as the most crucial drivers for fatigue during a nurse shift in an ICU.

Keywords: Fatigue-recovery simulation model · Intensive care unit · Hierarchical task analysis

1 Introduction

Within typical health organizations, nurses are the largest workforce and play a vital role in the quality of care and health promotion [1]. Generally, the nursing workload is determined by the time spent on patient care, nursing activities, and the skills needed to care for the patient. Nursing is physically and mentally strenuous, and high fatigue level is expected during the shift [2]. Fatigue and performance decrements are safety hazards for both patients and nurses in an intensive care unit (ICU). However, not many studies have been conducted on the connection between fatigue and nursing activities. Hence, this study is focused on the ICU nurses' workflow, which is analyzed based on three main characteristics: sequence of tasks under the same task group, frequency of the tasks, and tasks duration. The ICU is an environment that provides care for patients

with severe clinical conditions [1]. ICU nurses are exposed to extremely high workloads, both physically and mentally.

This study is based on the ICU nurses' workflow using the Near Field Electromagnetic Ranging (NFER) System and time study manual observation data collected during two different periods. The first period refers to February and March 2020, and the second one refers to July 2020. The tasks observed during the data collection were based on the task descriptions in a previous study [3]. NFER System is an indoor global positioning system. There are several applications to local positioning systems, particularly in healthcare. They are used to find assets, caregivers, and patients, implying less time needed to look for people and medical equipment, reduce inventory and labor, and increase patient satisfaction [4].

The motivation for this work is to advance our understanding of the impact of the key task groups of nursing activities and sequence of tasks on nurses' average fatigue level during a shift. For that reason, this study aims to analyze that impact by simulated experiments varying the frequencies and sequences of nursing tasks in a screening experiment. Then, the main goal is to find the frequency and sequence task configurations that turn out high levels of fatigue risk. In this study, the instantaneous fatigue level is measured as a function of the task duration and its fatigue index, which in its turn, depends upon how mental, physical, and effort (focus) demanding the task is. In this study, the fatigue index determines how much time a worker is completely exhausted if s/he conducts the task without interruption. During the working shift, nurses switch between periods of fatigue accumulation and a few recovery periods, such as lunchtime. The fatigue level is negatively correlated to the task recovery index during a recovery period.

Two HTA (Hierarchical Task Analysis) charts were developed to develop simulation models using the Micro Saint Sharp software. With the models, the main simulation outcomes were compared with the collected data, and since there was statistical evidence that the simulations represented the observed data, simulate fatigue in both. After that, the simulation models were run 1,000 times for screening experiments. Finally, the contribution of each key factor over fatigue level was investigated.

2 Literature Review

Fatigue can take many forms such as mental fatigue, lack of alertness, specific muscular fatigue, or general body fatigue [5]. Moreover, human factors modeling is concerned with muscular fatigue accumulation and recovery [6]. Different aspects of fatigue can be included in human reliability analysis to identify potential risks, such as mental demand, physical demand, period performing a task, performance, and effort.

Studies showed the association among fatigue, work schedules, and perceived work performance among nurses, investigating the work-related fatigue by the Occupational Fatigue Exhaustion Recovery (OFER 15) scale [2]. Despite some similarities with the present study, as both investigate the same work/fatigue relationship, the outcomes of these other studies do not provide any forecast of fatigue during a work shift. That is why the assessment of the impacts on nurses' fatigue level and workflow makes this work so innovative.

Studies correlate human error and the interactions learning–forgetting and fatigue–recovery analytically, using the mathematical modeling called the learning–forgetting–fatigue–recovery model, but that work is focused only on the interactions fatigue–recovery [7, 8]. The current study does not aim to find or predict any worker error rate, but as mentioned before, to assess the impacts on nurses’ fatigue level and work-flow, since fatigue is a safety hazard that has implications for both nurses and patients [2]. Other studies have applied the same mathematical model to simulate fatigue in a maintenance routine [9].

To calculate the accumulated fatigue, three levels of fatigue (or recovery) index are assumed, which determines how fast a worker gets exhausted (or recovers) under a work routine (or break): Slow, medium, and fast fatigue accumulation index levels [7]. The slow index assumes that the worker is completely exhausted after a 12-h working shift. Medium and fast indexes assume 8-h and 4-h working shifts, respectively. The recovery index has the same assumptions, that is, for the slow index, the worker will be completely recovered after a 12-h break, and so on. Since a normal ICU nurse shift lasts about 12 h, it is plausible to adopt the slow fatigue/recovery index.

2.1 National Aeronautics and Space Administration Task Load Index (NASA-TLX)

NASA-TLX is a subjective workload assessment tool that allows users to perform subjective workload assessments on a worker [10]. It derives an overall workload score based on a weighted average of ratings on six subscales, mental demand, physical demand, temporal demand, performance, effort, and frustration. In this study, a similar assessment tool was developed to define if an activity demands, is neutral to, or is invigorating in terms of mental demand, physical demand, and effort, qualitative analyzes instead of the quantitative NASA-TLX assessment.

3 Methodology

3.1 Data Collection

The data used in this study were collected using the same architecture applied in a previous study [3]. The NFER system was used to record the real-time location of nurses in an ICU, while the observers recorded the start time and end time of each task done by ICU. NFER technology is emerging as a preferred real-time locating system (RTLS) solution for operation in complicated indoor propagation environments, such as ICU [11]. NFER systems yield an accurate location within 1 m about 83% of the time, with the potential for 30 cm, which is completely acceptable for this study [12]. The NFER system architecture consists of tracking servers covering the whole ICU area, the tracking software installed in a laptop, and sensors that recognize nurses’ location by tags they carry during their shifts. The servers receive and process the data to calculate a position of a tag.

During the data collection, the observers followed and monitored nurses’ activities, recorded the start time and end time of each task done by them, and made notes for any special events during the observation. The observers organized the activities using the same codes used in a previous study [3].

3.2 Hierarchical Task Analysis

There are three principles governing the theory of Hierarchical Task Analysis (HTA) [13]. The first principle states that HTA is meant to describe a system in terms of its goals. The second principle is that HTA allows a system to be broken down into sub-operations in a hierarchical manner. The last principle refers to an existing relationship among goals and sub-goals, and the rules to achieve sub-goals and the final objective. Based on that description, the development of the HTA chart allowed to build the simulation models as closely as possible to the reality.

The data set of the two periods was organized in two HTA charts, representing the data from February, March 2020, and July 2020 periods. The HTA charts aim to represent the nurses' workflow as a function of two main characteristics. The first one is the task frequencies, which are the number of times a task is repeated during a shift. The HTA charts order the tasks as a function of the greatest frequencies within each group of activities. The second feature refers to the task sequences, and the HTA charts reproduce those by the accomplishment plans for each group or subgroups of tasks.

The HTA charts organize both period workflows in the same seven main activity categories: Handoff, In-room activities, Out-of-room activities, Peer support, Patient clinical processes conversations, Teaching residents/students, and Non-nursing activities. However, the activities within the main tasks are placed in a different order for each period as a function of their frequencies, from the highest to the lowest one.

Handoff activity happens when the off-going nurses provide the oncoming nurse with a detailed review of the important issues about the patient's health condition. In-room activities contain all tasks performed inside the patient room and the tasks that support those kinds of activities. Out-of-room activities, as in-room activities, are related to patient care, but they are performed out of the patient rooms. Peer support activities, like the in-room activities, are conducted in the patient rooms, but this time the ICU nurse works as a peer supporter. Patient clinical processes conversations are related to patient care, but the patients are not part of those activities. As the data was collected at the University of Missouri Hospital, teaching residents/students are part of nurses' duties. Finally, non-nursing activities refer to all activities unrelated to patient care.

3.3 Simulation Model

The developed HTA charts are the foundation for developing two discrete event simulation models, one for each period, using the Micro Saint Sharp software. Discrete event simulation has been a standard technique in system analysis for more than 50 years [14]. Micro Saint Sharp program has been used in the health care industry, human factors, and ergonomics. While the simulation models were running, every time a task was accomplished, it calculated the nurse fatigue level and its contribution to the average fatigue level. Figure 1 shows an example of fatigue level outcome based on the Fatigue and Recovery effects. It also shows the nurse's average fatigue level for that shift.

3.4 Design of Experiment

The model-dependent variable is nurses' average fatigue level. This study aims to analyze its pattern by simulated experiments that randomly vary all nursing task frequencies

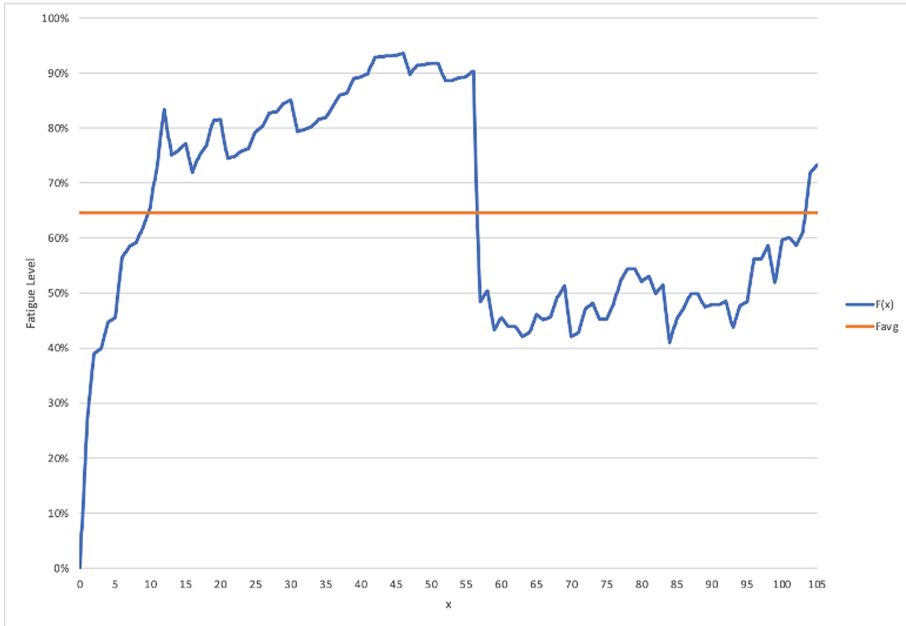


Fig. 1. Fatigue and Recovery effects during a shift.

and sequences, the independent variables, in a screening experiment. Besides the frequency variables, this study uses two independent sequence variables: the number of task sequences before lunch (seq_0) and after lunch (seq_1). A task sequence lasts while a nurse is conducting any activity related to the patient care, be it inside or outside the patient room, is supporting a peer, or is talking with someone else about a patient clinical condition. The task sequence finishes when the nurse initiates any non-value added activity. It is essential to clarify that if a nurse conducts 100 nursing activities during 5 task sequences in a shift, it averages 20 tasks/sequence. On the other hand, for the same 100 activities, but using 10 task sequences, it turns out 10 tasks/sequence. For a 12-h shift, the greater the number of task sequences, the greater the number of breaks between them.

For the experiment's accuracy, several adjustments were made. The three tasks (i.e., performing procedure, patient care, and closed curtain) were combined in one new variable, called *pc*. Also, the tasks within the category peer support were combined in the variable, called *ps*. Finally, tasks that might happen in- or out-of-room were counted together, such as EMR charting that turns out *emr*, using ASCOM phone that turns out *ascom*, talking with a physician that turns out *twp*, and talking with patient's family that turns out *twf*.

Each simulation model runs 1,000 times, and the simulated data were analyzed using JMP software, which turns out the response prediction expression (see Eq. 1). All independent variables were standardized using the transformation in Eq. 2. That transformation makes all independent variables have mean = 0 and standard deviation = 1, and the benefits of that are: $\hat{\beta}_0$ represents the average response and the estimated

coefficients represent their variables' impact over the response, that is, the greater the coefficient, the larger the effect on the response.

$$\hat{F}_{avg} = \hat{\beta}_0 + \sum_{i=1}^n \hat{\beta}_i z_i + \sum \sum_{i < j} \hat{\beta}_{ij} z_i z_j, \begin{cases} i = 1, 2, \dots, n. \\ j = 1, 2, \dots, n. \end{cases} \tag{1}$$

where:

\hat{F}_{avg} = estimated average fatigue level during a shift.

$\hat{\beta}_0$ = intercept (average response).

$\hat{\beta}_i$ = estimated coefficients for the main effects.

$\hat{\beta}_{ij}$ = estimated coefficient for the main effect interactions.

z_i = standardized independent variables.

n = number of independent variables.

$$z_{i,r} = \frac{x_{i,r} - \bar{x}_i}{S_i} \tag{2}$$

where:

$z_{i,r}$ = standardized variable z_i at run r .

$x_{i,r}$ = variable x_i at run r .

\bar{x}_i = mean for variable x_i .

S_i = standard deviation for variable x_i .

4 Results

Average Fatigue Level. Two experiments, simulating the average fatigue level reached during a shift, were conducted with 1,000 runs for each period. This number of runs is significant enough to use the significance level of 0.01. It does not increase the probability of mistakenly concluding that both periods present the same average fatigue level pattern when they do not. Table 1 shows that the average fatigue level is different between the periods of interest ($\alpha = 0.01$), with the average fatigue level for the Feb, Mar-20 shifts being higher than the Jul-20 shifts.

Table 1. Comparison between simulated average fatigue level for Feb, Mar-20 and Jul-20 models.

Period	Average fatigue level	SD	Statistic	p
Feb, Mar-20	0.636	0.070	2.758	0.006
Jul-20	0.627	0.069		

Average Fatigue Level Screening. Although the models are different in their average fatigue level, they have some similarities. They have in common that *seq₀*, *seq₁*, *pc*, and *ps* variables are significant in both periods, outstanding as the most important drivers of fatigue for nurses.

Feb, Mar-20 Model

Equation 3 is the predicted average fatigue level as a function of the most significant independent variables ($p = 0.01$).

$$\hat{F}_{avg} = 0.636 - 0.040z_{seq_1} - 0.039z_{seq_0} + 0.010z_{pc} + 0.009z_{emr} + 0.008z_{ps} + 0.005z_{twf} + 0.004z_{pc_1} \quad (3)$$

Table 2 presents the most significant independent variables for the significance level of 0.01, in order of significance.

Table 2. Standardized parameter estimates (Feb, Mar-20 model).

Variable	Confidence interval	P
<i>seq₁</i>	[-0.041, -0.038]	<0.001
<i>seq₀</i>	[-0.041, -0.038]	<0.001
<i>pc</i>	[0.009, 0.012]	<0.001
<i>emr</i>	[0.007, 0.010]	<0.001
<i>ps</i>	[0.007, 0.009]	<0.001
<i>twf</i>	[0.003, 0.006]	0.0008
<i>pc₁</i>	[0.003, 0.006]	0.0024

Also, Eq. 3 tells that, for the variable *seq₁*, an increment of 1 standard deviation decreases the average fatigue level in 0.04, or it may be as great as 0.041 or as low as 0.038 (Table 2). For the variable *seq₀*, an increment of 1 standard deviation decreases the average fatigue level in 0.039, or it may be as great as 0.041 or as low as 0.038. For the variable *pc*, an increment of 1 standard deviation increases the average fatigue level in 0.01, or it may be as low as 0.009 or as great as 0.012. For the variable *emr*, an increment of 1 standard deviation increases the average fatigue level in 0.009, or it may be as low as 0.007 or as great as 0.010. For the variable *ps*, an increment of 1 standard deviation increases the average fatigue level in 0.008, or it may be as low as 0.007 or as great as 0.009. For the variable *twf*, an increment of 1 standard deviation increases the average fatigue level in 0.005, or it may be as low as 0.003 or as great as 0.006. For the variable *pc₁*, an increment of 1 standard deviation increases the average fatigue level in 0.004, or it may be as low as 0.003 or as great as 0.006.

Jul-20 Model

Equation 4 is the predicted average fatigue level as function of the most significant independent variables ($p = 0.01$).

$$\hat{F}_{avg} = 0.627 - 0.036z_{seq_1} - 0.033z_{seq_0} + 0.018z_{pc} + 0.012z_{ps} + 0.006z_{pc_1} \quad (4)$$

Table 3 presents the most significant independent variables for the significance level of 0.01, in order of significance.

Table 3. Standardized parameter estimates (Jul-20 model).

Variable	Confidence interval	P
<i>seq</i> ₁	[-0.037, -0.034]	<0.001
<i>seq</i> ₀	[-0.035, -0.031]	<0.001
<i>pc</i>	[0.016, 0.019]	<0.001
<i>ps</i>	[0.010, 0.013]	<0.001
<i>pc</i> ₁₂	[0.005, 0.008]	<0.001

Also, Eq. 4 tells that, for the variable *seq*₁, an increment of 1 standard deviation decreases the average fatigue level in 0.036, or it may be as great as 0.037 or as low as 0.034. For the variable *seq*₀, an increment of 1 standard deviation decreases the average fatigue level in 0.033, or it may be as great as 0.035 or as low as 0.031. For the variable *pc*, an increment of 1 standard deviation increases the average fatigue level in 0.018, or it may be as low as 0.016 or as great as 0.019. For the variable *ps*, an increment of 1 standard deviation increases the average fatigue level in 0.012, or it may be as low as 0.01 or as great as 0.013. For the variable *pc*₁₂, an increment of 1 standard deviation increases the average fatigue level in 0.006, or it may be as low as 0.005 or as great as 0.008.

The variable *pc* is a significant fatigue driver in both periods and the differences presented in the dataset are not. The variable *ps* is other type of tasks that are important fatigue drivers in both periods and do not present significant differences between. The exception here is the number of patient transportation activities (*pc*₁₂) that do not present significant differences between periods, but it is only a significant fatigue driver for July 2020, which requires further investigation.

On the other hand, the variable *emr* is relevant only for the Feb, Mar-20 model, and when the periods' patterns are compared to each other, it is possible to identify that it decreased 16.5% in average during July 2020. Moreover, it is possible to identify the same pattern in the variable *twf*, that decreased 74.3% in average, and the variable *pc*₁, that decreased 72.2% in average, during July 2020.

Although the number of patient transportation activities does not present significant differences between periods, during the July 2020, that type of activity was, on average, more than 3 times longer than during February to March 2020.

5 Discussion

The main contribution of this study is that we identified three main factors influencing nurses' fatigue in an ICU shift: 1) the number of tasks conducted in a sequence without a break (number of task sequences), 2) the number of patient care or procedures, and 3) peer

support activities performed during the shift. Besides knowing the key factors responsible for nurse's fatigue levels during an ICU shift in each period, it is also important to understand why some of them are present in both periods or in only one and how they differ in impact magnitude in both periods, recalling that July 2020 was in the middle of the COVID-19 pandemic and when new resident physicians began working in the hospital (an annual event in hospitals in the United States).

The total number of activities conducted during a shift was higher from February to March 2020. Since the shifts in both periods have the same average duration of 12 h, that suggests that nurses might spend longer time in non-valuable activities during July 2020, which explains why the average fatigue level of the data from February to March 2020 was slightly higher than July 2020 (see Table 1).

Recalling that the ICU in this study is a non-COVID-19 unit, and other studies have shown that non-COVID units became less busy during the pandemic in some health care units around the world, e.g., in a hospital in Denmark, admissions for all non-COVID-19 disease groups decreased during compared with the pre-pandemic period [15]. Moreover, studies have found that non-COVID medical emergencies nearly halved during the British lockdown [16]. Also added, social distancing may have heralded the significant reductions in non-COVID and non-pneumonic infections in 2020 compared with 2017. Other studies also reinforce that non-COVID-19 ICUs have been less busy during the pandemic, insofar as changes in working patterns reduce risks associated with both long working hours and shift working [17]. It is worthwhile to mention that this concentrated effort on COVID-19 units could have entailed an increment of out-of-hospital mortality due to non-COVID diseases, particularly during the lockdown weeks [18].

The number of times tasks are conducted continuously without a break (number of task sequences), both before and after lunch, are the most significant factors to nurses' fatigue during a shift in an ICU for both periods. It is worthwhile mentioning that for a 12-h shift, the larger the number of task sequences, the shorter the sequences and the more often breaks occurred between them. For example, if during a shift, a nurse conducts 100 tasks using 5 task sequences, it turns out in average 20 tasks/sequence. On the other hand, for the same 100 tasks, but using 10 task sequences, it turns out 10 tasks/sequence. There was a negative correlation between the number of task sequences and the nurse's average fatigue level. This study also shows that the total number of activities during a period magnifies the effect of the number of task sequences. While during the first period (February to March 2020), when the nurses were busier, Eq. 3 shows that, for the variable seq_1 , an increment of 1 standard deviation over the mean decreases the average fatigue level in 0.04, and for the variable seq_0 , an increment of 1 standard deviation over the mean decreases the average fatigue level in 0.039, during the second period (July 2020), when nurses were less busy, Eq. 4 shows that, for the variable seq_1 , an increment of 1 standard deviation over the mean decreases the average fatigue level in 0.036, and for the variable seq_0 , an increment of 1 standard deviation over the mean decreases the average fatigue level in 0.033. The sequence length may explain this effect, given that during the first period (February to March 2020), in average nurse used to perform a total of 154.457 tasks in 19.327 task sequences (before and after lunch together). During the second period (July 2020), a total of 139.8 tasks in 21.106 task sequences (before

and after lunch together), it turns out an average of 7.99 tasks/sequence during the first period (February to March 2020) and of 6.62 tasks/sequence during the second period.

The variables related to tasks' frequencies are positively correlated to nurses' fatigue levels, and in periods when nurses were less busy, as during the second period (July 2020), an increase in the number of tasks impacts more the nurses' fatigue than during periods when the nurses were busier, as in the first period (February to March 2020). For example, the variables *pc* and *ps* are significant for both periods and have coefficient estimates of 0.01 (Eq. 3) and 0.018 (Eq. 4) for Feb, Mar-20 and Jul-20 models, respectively. Moreover, it makes sense that those variables are significant in both models, since those activities do not present significant differences between periods.

However, some variables are significant in only one model. For instance, the variable *emr* is significant only for the Feb, Mar-20 model. So, in a further investigation, it is possible to note that during the Feb, Mar-20 period, nurses conducted more EMR charting activities than during the second period (July 2020). Similarly, the variable *twf*, the number of times the nurse talks to a patient's family, is also greater during the first period (February to March 2020) compared to the second one (July 2020). And lastly, the variable *pc₁*, the number of initial assessments, is also significant only for the first period (February to March 2020), when there was much more of this type of task than in the second one (July 2020). This pattern suggests that during the second period (July 2020), those variables' frequency ranges are not enough to impact the nurses' average fatigue level. Moreover, that observed difference should be strongly correlated to the need to avoid unnecessary contact with patients during the COVID-19 pandemic, that is, avoiding unnecessary contact with patients to prevent any contaminations, as described by precautionary measures that were disseminated during the pandemic [19]. Besides, during the pandemic, the nurses talked with the patient's family much less than before. This data suggests that during the pandemic, the access of patients' families to the hospital decreased considerably because of organizational visiting policy changes.

The only observed exception was that the variable *pc₁₂*, the number of times the nurse transported or prepared a patient to be transported, does not present significant differences in terms of frequency between periods, but it is only significant for the Jul-20 model. In a further investigation, it is possible to verify that during Jul-20, the time associated with the variable *pc₁₂* was much longer than during the first period (February to March 2020). This difference might not be related to whether the data is from the first period (February to March 2020) or second one (July 2020), but rather to the patients' clinical conditions in those specific periods, that is, the duration that a healthcare team takes to transport a patient might not be related to the period of the year the patient is in the ICU, but rather to the patient's clinical condition.

As previously mentioned, the number of sequences conducted in a shift is the most significant factor that leads to fatigue during a nurse ICU shift. Besides the number of sequences, both models have the variables *pc* and *ps* as fatigue drivers.

As the limitations of this study, the dataset does not present the ratio number of nurses/number of patients during the shifts, and these ratios might be strongly correlated to those variables. Therefore, it is recommended to include the ratios as an independent variable in the model. Another limitation in this study is regarding the fatigue and recovery indexes. In our current simulation models, we assumed three levels for the

indexes (i.e., low, medium, and high) depending on the nature of the activity. Hence, it is recommended to capture a more precise fatigue and recovery index to improve our simulation results.

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